Information Extraction

Libraries

```
# libraries
import PyPDF2
import pandas as pd
import nltk
#nltk.download("punkt")
import re

import spacy
# only for datalore
import subprocess
#%%
print(subprocess.getoutput("python -m spacy download en_core_web_sm"))

nlp = spacy.load("en_core_web_sm")

import textacy
import summa
from summa import keywords

from snorkel.preprocess import preprocessor
from snorkel.types import DataPoint
from itertools import combinations
from snorkel.labeling import labeling_function
from snorkel.labeling import PandasLFApplier

import networkx as nx
from matplotlib import pyplot as plt
```

```
Defaulting to user installation because normal site-packages is not
writeable
Collecting en-core-web-sm==3.7.1
  Downloading
https://github.com/explosion/spacy-models/releases/download/en_core_we
b_sm-3.7.1/en_core_web_sm-3.7.1-py3-none-any.whl (12.8 MB)
     ---------------------------------------- 0.0/12.8 MB ? eta
-:--:--
     - -------------------------------------- 0.4/12.8 MB 7.4 MB/s eta
0:00:02
     -- ------------------------------------- 0.9/12.8 MB 9.2 MB/s eta
0:00:02
     ---- ----------------------------------- 1.4/12.8 MB 9.7 MB/s eta
0:00:02
     ----- ---------------------------------- 1.9/12.8 MB 10.1 MB/s
eta 0:00:02
```

```
     ------- -------------------------------- 2.4/12.8 MB 10.4 MB/s
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eta 0:00:01
     ---------- ----------------------------- 3.5/12.8 MB 11.1 MB/s
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     -------------------- ------------------- 6.6/12.8 MB 11.1 MB/s
eta 0:00:01
     ---------------------- ----------------- 7.1/12.8 MB 11.1 MB/s
eta 0:00:01
     ----------------------- ---------------- 7.6/12.8 MB 11.1 MB/s
eta 0:00:01
     ------------------------- -------------- 8.2/12.8 MB 11.3 MB/s
eta 0:00:01
     --------------------------- ------------ 8.7/12.8 MB 11.3 MB/s
eta 0:00:01
     ---------------------------- ----------- 9.2/12.8 MB 11.3 MB/s
eta 0:00:01
     ------------------------------ --------- 9.7/12.8 MB 11.3 MB/s
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     ------------------------------- ------- 10.2/12.8 MB 11.3 MB/s
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     -------------------------------- ------ 10.8/12.8 MB 11.5 MB/s
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     ------------------------------------- - 12.4/12.8 MB 11.5 MB/s
eta 0:00:01
     --------------------------------------  12.8/12.8 MB 11.5 MB/s
eta 0:00:01
     --------------------------------------- 12.8/12.8 MB 11.1 MB/s
eta 0:00:00
Requirement already satisfied: spacy<3.8.0,>=3.7.2 in c:\users\user7\
appdata\roaming\python\python39\site-packages (from en-core-web-
sm==3.7.1) (3.7.4)
Requirement already satisfied: spacy-legacy<3.1.0,>=3.0.11 in c:\
users\user7\appdata\roaming\python\python39\site-packages (from
```

```
spacy<3.8.0,>=3.7.2->en-core-web-sm==3.7.1) (3.0.12)
Requirement already satisfied: spacy-loggers<2.0.0,>=1.0.0 in c:\
users\user7\appdata\roaming\python\python39\site-packages (from
spacy<3.8.0,>=3.7.2->en-core-web-sm==3.7.1) (1.0.5)
Requirement already satisfied: murmurhash<1.1.0,>=0.28.0 in c:\users\
user7\appdata\roaming\python\python39\site-packages (from
spacy<3.8.0,>=3.7.2->en-core-web-sm==3.7.1) (1.0.10)
Requirement already satisfied: cymem<2.1.0,>=2.0.2 in c:\users\user7\
appdata\roaming\python\python39\site-packages (from
spacy<3.8.0,>=3.7.2->en-core-web-sm==3.7.1) (2.0.8)
Requirement already satisfied: preshed<3.1.0,>=3.0.2 in c:\users\
user7\appdata\roaming\python\python39\site-packages (from
spacy<3.8.0,>=3.7.2->en-core-web-sm==3.7.1) (3.0.9)
Requirement already satisfied: thinc<8.3.0,>=8.2.2 in c:\users\user7\
appdata\roaming\python\python39\site-packages (from
spacy<3.8.0,>=3.7.2->en-core-web-sm==3.7.1) (8.2.3)
Requirement already satisfied: wasabi<1.2.0,>=0.9.1 in c:\users\user7\
appdata\roaming\python\python39\site-packages (from
spacy<3.8.0,>=3.7.2->en-core-web-sm==3.7.1) (1.1.2)
Requirement already satisfied: srsly<3.0.0,>=2.4.3 in c:\users\user7\
appdata\roaming\python\python39\site-packages (from
spacy<3.8.0,>=3.7.2->en-core-web-sm==3.7.1) (2.4.8)
Requirement already satisfied: catalogue<2.1.0,>=2.0.6 in c:\users\
user7\appdata\roaming\python\python39\site-packages (from
spacy<3.8.0,>=3.7.2->en-core-web-sm==3.7.1) (2.0.10)
Requirement already satisfied: weasel<0.4.0,>=0.1.0 in c:\users\user7\
appdata\roaming\python\python39\site-packages (from
spacy<3.8.0,>=3.7.2->en-core-web-sm==3.7.1) (0.3.4)
Requirement already satisfied: typer<0.10.0,>=0.3.0 in c:\users\user7\
appdata\roaming\python\python39\site-packages (from
spacy<3.8.0,>=3.7.2->en-core-web-sm==3.7.1) (0.9.0)
Requirement already satisfied: smart-open<7.0.0,>=5.2.1 in c:\users\
user7\appdata\roaming\python\python39\site-packages (from
spacy<3.8.0,>=3.7.2->en-core-web-sm==3.7.1) (6.4.0)
Requirement already satisfied: tqdm<5.0.0,>=4.38.0 in c:\program
files\python39\lib\site-packages (from spacy<3.8.0,>=3.7.2->en-core-
web-sm==3.7.1) (4.66.1)
Requirement already satisfied: requests<3.0.0,>=2.13.0 in c:\program
files\python39\lib\site-packages (from spacy<3.8.0,>=3.7.2->en-core-
web-sm==3.7.1) (2.31.0)
Requirement already satisfied: pydantic!=1.8,!=1.8.1,<3.0.0,>=1.7.4 in
c:\program files\python39\lib\site-packages (from spacy<3.8.0,>=3.7.2-
>en-core-web-sm==3.7.1) (2.5.2)
Requirement already satisfied: jinja2 in c:\program files\python39\
lib\site-packages (from spacy<3.8.0,>=3.7.2->en-core-web-sm==3.7.1)
(3.1.2)
Requirement already satisfied: setuptools in c:\program files\
python39\lib\site-packages (from spacy<3.8.0,>=3.7.2->en-core-web-
sm==3.7.1) (58.1.0)
```

```
Requirement already satisfied: packaging>=20.0 in c:\program files\
python39\lib\site-packages (from spacy<3.8.0,>=3.7.2->en-core-web-
sm==3.7.1) (23.2)
Requirement already satisfied: langcodes<4.0.0,>=3.2.0 in c:\users\
user7\appdata\roaming\python\python39\site-packages (from
spacy<3.8.0,>=3.7.2->en-core-web-sm==3.7.1) (3.3.0)
Requirement already satisfied: numpy>=1.19.0 in c:\program files\
python39\lib\site-packages (from spacy<3.8.0,>=3.7.2->en-core-web-
sm==3.7.1) (1.26.2)
Requirement already satisfied: annotated-types>=0.4.0 in c:\program
files\python39\lib\site-packages (from pydantic!=1.8,!
=1.8.1,<3.0.0,>=1.7.4->spacy<3.8.0,>=3.7.2->en-core-web-sm==3.7.1)
(0.6.0)
Requirement already satisfied: pydantic-core==2.14.5 in c:\program
files\python39\lib\site-packages (from pydantic!=1.8,!
=1.8.1,<3.0.0,>=1.7.4->spacy<3.8.0,>=3.7.2->en-core-web-sm==3.7.1)
(2.14.5)
Requirement already satisfied: typing-extensions>=4.6.1 in c:\program
files\python39\lib\site-packages (from pydantic!=1.8,!
=1.8.1,<3.0.0,>=1.7.4->spacy<3.8.0,>=3.7.2->en-core-web-sm==3.7.1)
(4.9.0)
Requirement already satisfied: charset-normalizer<4,>=2 in c:\program
files\python39\lib\site-packages (from requests<3.0.0,>=2.13.0-
>spacy<3.8.0,>=3.7.2->en-core-web-sm==3.7.1) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in c:\program files\
python39\lib\site-packages (from requests<3.0.0,>=2.13.0-
>spacy<3.8.0,>=3.7.2->en-core-web-sm==3.7.1) (3.6)
Requirement already satisfied: urllib3<3,>=1.21.1 in c:\program files\
python39\lib\site-packages (from requests<3.0.0,>=2.13.0-
>spacy<3.8.0,>=3.7.2->en-core-web-sm==3.7.1) (2.1.0)
Requirement already satisfied: certifi>=2017.4.17 in c:\program files\
python39\lib\site-packages (from requests<3.0.0,>=2.13.0-
>spacy<3.8.0,>=3.7.2->en-core-web-sm==3.7.1) (2023.11.17)
Requirement already satisfied: blis<0.8.0,>=0.7.8 in c:\users\user7\
appdata\roaming\python\python39\site-packages (from
thinc<8.3.0,>=8.2.2->spacy<3.8.0,>=3.7.2->en-core-web-sm==3.7.1)
(0.7.11)
Requirement already satisfied: confection<1.0.0,>=0.0.1 in c:\users\
user7\appdata\roaming\python\python39\site-packages (from
thinc<8.3.0,>=8.2.2->spacy<3.8.0,>=3.7.2->en-core-web-sm==3.7.1)
(0.1.4)
Requirement already satisfied: colorama in c:\program files\python39\
lib\site-packages (from tqdm<5.0.0,>=4.38.0->spacy<3.8.0,>=3.7.2->en-
core-web-sm==3.7.1) (0.4.6)
Requirement already satisfied: click<9.0.0,>=7.1.1 in c:\program
files\python39\lib\site-packages (from typer<0.10.0,>=0.3.0-
>spacy<3.8.0,>=3.7.2->en-core-web-sm==3.7.1) (8.1.7)
Requirement already satisfied: cloudpathlib<0.17.0,>=0.7.0 in c:\
users\user7\appdata\roaming\python\python39\site-packages (from
```

```
weasel<0.4.0,>=0.1.0->spacy<3.8.0,>=3.7.2->en-core-web-sm==3.7.1)
(0.16.0)
Requirement already satisfied: MarkupSafe>=2.0 in c:\program files\
python39\lib\site-packages (from jinja2->spacy<3.8.0,>=3.7.2->en-core-
web-sm==3.7.1) (2.1.3)
вњ” Download and installation successful
You can now load the package via spacy.load('en_core_web_sm')
```

Import Text

```
# creating a pdf file object
# pdfFileObj = open('The_Shadow_Over_Innsmouth.pdf', 'rb')
pdfFileObj = open('2024.pdf', 'rb')

# creating a pdf reader object
pdfReader = PyPDF2.PdfReader(pdfFileObj)

# how many pages
len(pdfReader.pages)

print(len(pdfReader.pages))

# creating a page object
pageObj = pdfReader.pages

# extracting text from page
# loop here to get it all
text = []
for page in pageObj:
  text.append(page.extract_text())

# closing the pdf file object
pdfFileObj.close()

18
```

Convert to Sentences and Pandas

- ^ means start with
- [0-9] means any of these digits
- [a-zA-Z] means any alpha latin character lower or upper case
- $ ends with
- . mean any character

  o means zero or more of the previous character (so .* means zero or more of any character)

```
# create a place to save the text
saved_words = []

# Joining the extracted text pages into a single string
book = ' '.join(text)

# loop over each word
for word in nltk.word_tokenize(book):
    # if the word starts with a number and ends with a letter
    if (re.search(r'^[0-9].*[a-zA-Z]$', word) != "None"):
        # take out the numbers and save into our text
        saved_words.append(re.sub(r'[0-9]', '', word))
    # if not then save just the word
    else:
        saved_words.append(word)

book =' '.join(saved_words)

DF = pd.DataFrame(
    nltk.sent_tokenize(book),
    columns = ["sentences"]
)

DF.head()

# for IE, we want sentence and/or paragraph level structure
```

	sentences
0	Data science interview questions and answers f...
1	We encourage you to go through the curated lis...
2	Apply as data scientists I 'm hiring developer...
3	As a vast field , with plenty of demand , both...
4	Hence , to prepare both parties , we have cura...

Part of Speech Tagging

- Tag your data with spacy's part of speech tagger.
- Convert this data into a Pandas DataFrame.

```
# easier to loop over the big text file than loop over words AND rows
in pandas
spacy_pos_tagged = [(str(word), word.tag_, word.pos_) for word in
nlp(book)]
# each row represents one token
DF_POS = pd.DataFrame(
    spacy_pos_tagged,
    columns = ["token", "specific_tag", "upos"]
)
```

- Use the dataframe to calculate the most common parts of speech.

```
DF_POS['upos'].value_counts()
```

```
upos
NOUN      1223
PUNCT      526
VERB       514
DET        466
ADP        428
ADJ        340
AUX        301
PROPN      229
PRON       168
CCONJ      137
PART        92
ADV         72
SCONJ       68
NUM         55
SPACE       45
X           16
SYM          9
INTJ         8
Name: count, dtype: int64
```

- Use the dataframe to calculate if words are considered more than one part of speech (crosstabs or groupby).

```
DF_POS2 = pd.crosstab(DF_POS['token'], DF_POS['upos'])
# convert to true false to add up how many times not zero
DF_POS2['total'] = DF_POS2.astype(bool).sum(axis=1)
#print out the rows that aren't 1
DF_POS2[DF_POS2['total'] > 1]
```

```
upos      ADJ  ADP  ADV  AUX   CCONJ  DET  INTJ  NOUN  NUM  PART  PRON
PROPN  \
token

+           0    0    0    0      0    0     0     0    1     0     0
1
-           0    0    0    0      0    0     0     0    0     0     0
1
-based      1    0    0    0      0    0     0     0    0     0     0
0
-means      0    0    0    0      0    0     0     2    0     0     0
3
-square     1    0    0    0      0    0     0     1    0     0     0
0
...       ...  ...  ...  ...    ...  ...   ...   ...  ...   ...   ...
...
to          0   25    0    0      0    0     0     0    0    79     0
0
```

```
training     0    0    0    0      0    0     0     3    0     0     0
0
use          0    0    0    0      0    0     0     1    0     0     0
0
which        0    0    0    0      0    1     0     0    0     0     5
0
•            0    1    0    0      0    0     0     0   19     0     2
0

upos       PUNCT  SCONJ  SPACE  SYM  VERB  X  total
token
+              0      0      0    0     0  0      2
-              6      0      0    0     0  0      2
-based         0      0      0    0     1  0      2
-means         0      0      0    0     0  0      2
-square        0      0      0    0     0  0      2
...          ...    ...    ...  ...   ... ..    ...
to             0      0      0    0     0  0      2
training       0      0      0    0     4  0      2
use            0      0      0    0    10  0      2
which          0      0      0    0     0  0      2
•              0      0      0    0     2  5      5

[97 rows x 19 columns]
```

- What is the most common part of speech? ANSWER THIS IN YOUR TEXT
- Do you see words that are multiple parts of speech? ANSWER THIS IN YOUR TEXT

KPE

- Use textacy to find the key phrases in your text.

  o in the r window for r people

  o library(reticulate)

  o py_install("networkx < 3.0", pip = T)

```
# textacy KPE
# build an english language for textacy pipe
en = textacy.load_spacy_lang("en_core_web_sm", disable=("parser"))

# build a processor for textacy using spacy and process text
doc = textacy.make_spacy_doc(book, lang = en)

# text rank algorithm
print([kps for kps, weights in textacy.extract.keyterms.textrank(doc,
normalize = "lemma",  topn = 5)])

terms = set([term for term, weight in
```

```
textacy.extract.keyterms.textrank(doc)])
print(textacy.extract.utils.aggregate_term_variants(terms))

['content Basic datum science interview question', 'datum science technical interview question', 'intermediate datum science interview question', 'advanced datum science interview question', 'datum science job']
[{'content Basic datum science interview question'}, {'intermediate datum science interview question'}, {'datum science technical interview question'}, {'advanced datum science interview question'}, {'exploratory datum analysis'}, {'datum science application'}, {'datum science life cycle'}, {'different datum type'}, {'datum science job'}, {'sample datum'}]
```

• Use summa to find the key phrases in your text.

```
TR_keywords = keywords.keywords(book, scores = True)
print(TR_keywords[0:10])

[('data science interview questions', 0.22221301412918812), ('sampling', 0.14684813577795505), ('sample', 0.14684813577795505), ('samplings', 0.14684813577795505), ('samples', 0.14684813577795505), ('variables', 0.14487282640726087), ('variable', 0.14487282640726087), ('values', 0.1339291369649484), ('value', 0.1339291369649484), ('methods', 0.12859857435603242)]
```

- What differences do you see in their outputs? COMMENT ON HOW SLOW!
- Using textacy utilities, combine like key phrases. SEE ABOVE
- Do the outputs make sense given your text? ANSWER THIS QUESTION

NER + Snorkel

- Use spacy to extract named entities.
- Create a summary of your named entities.

```
# easier to loop over the big text file than loop over words AND rows in pandas
spacy_ner_tagged = [(str(word.text), word.label_) for word in nlp(book).ents]

# each row represents one token
DF_NER = pd.DataFrame(
    spacy_ner_tagged,
    columns = ["token", "entity"]
)
print(DF_NER['entity'].value_counts())

DF_NER2 = pd.crosstab(DF_NER['token'], DF_NER['entity'])
print(DF_NER2)
```

```
# convert to true false to add up how many times not zero
DF_NER2['total'] = DF_NER2.astype(bool).sum(axis=1)
#print out the rows that aren't 1
DF_NER2[DF_NER2['total'] > 1]
```

```
entity
ORG             38
CARDINAL        30
PERSON          14
PRODUCT         10
GPE              9
NORP             3
WORK_OF_ART      3
LOC              2
ORDINAL          2
DATE             2
EVENT            1
Name: count, dtype: int64
entity                                                    CARDINAL  DATE
EVENT  \
token

AI                                                               0     0
0
ANOVA                                                            0     0
0
Algorithm                                                        0     0
0
Apply Now INTERMEDIATE DATA SCIENCE INTERVIEW Q...               0     0
0
Apply Now WRAPPING UP                                            0     0
1
...                                                            ...   ...
...
• Non                                                            0     0
0
• Recursive                                                      0     0
0
• Repeat                                                         0     0
0
• Select                                                         0     0
0
• Wrapper                                                        0     0
0

entity                                                    GPE  LOC  NORP
ORDINAL  \
token

AI                                                          0    0     0
```

```
0
ANOVA                                                  0    0     0
0
Algorithm                                              0    0     0
0
Apply Now INTERMEDIATE DATA SCIENCE INTERVIEW Q...     0    0     0
0
Apply Now WRAPPING UP                                  0    0     0
0
...                                                  ...  ...   ...
...
• Non                                                  0    0     0
0
• Recursive                                            0    0     0
0
• Repeat                                               0    0     0
0
• Select                                               0    0     0
0
• Wrapper                                              0    0     0
0

entity                                               ORG  PERSON
PRODUCT  \
token

AI                                                     1       0
0
ANOVA                                                  2       0
0
Algorithm                                              0       0
1
Apply Now INTERMEDIATE DATA SCIENCE INTERVIEW Q...     0       0
1
Apply Now WRAPPING UP                                  0       0
0
...                                                  ...     ...       .
..
• Non                                                  1       0
0
• Recursive                                            0       0
1
• Repeat                                               1       0
0
• Select                                               0       0
1
• Wrapper                                              0       0
1

entity                                               WORK_OF_ART
```

```
token
AI                                                              0
ANOVA                                                           0
Algorithm                                                       0
Apply Now INTERMEDIATE DATA SCIENCE INTERVIEW Q...              0
Apply Now WRAPPING UP                                           0
...                                                           ...
• Non                                                           0
• Recursive                                                     0
• Repeat                                                        0
• Select                                                        0
• Wrapper                                                       0

[67 rows x 11 columns]

entity        CARDINAL  DATE  EVENT  GPE  LOC  NORP  ORDINAL  ORG
PERSON  \
token

Data Science         0     0      0    0    0     0        0    1
1

entity        PRODUCT  WORK_OF_ART  total
token
Data Science        0            0      2
```

- Apply Snorkel to your data to show any relationship between names.

get the data into a good format

```
stored_entities = []

# first get the entities, must be two for relationship matches
def get_entities(x):
  """
  Grabs the names using spacy's entity labeler
  """
  # get all the entities in this row
  processed = nlp(x)
  # get the tokens for each sentence
  tokens = [word.text for word in processed]
  # get all the entities - notice this is only for persons
  temp = [(str(ent), ent.label_) for ent in processed.ents if
ent.label_ != ""]
  # only move on if this row has at least two
  if len(temp) > 1:
    # finds all the combinations of pairs
    temp2 = list(combinations(temp, 2))
    # for each pair combination
    for (person1, person2) in temp2:
```

```
      # find the names in the person 1
      person1_words = [word.text for word in nlp(person1[0])]
      # find the token numbers for person 1
      person1_ids = [i for i, val in enumerate(tokens) if val in
person1_words]
      # output in (start, stop) token tuple format
      if len(person1_words) > 1:
        person1_ids2 = tuple(idx for idx in person1_ids[0:2])
      else:
        id_1 = [idx for idx in person1_ids]
        person1_ids2 = (id_1[0], id_1[0])

      # do the same thing with person 2
      person2_words = [word.text for word in nlp(person2[0])]
      person2_ids = [i for i, val in enumerate(tokens) if val in
person2_words[0:2]]
      if len(person2_words) > 1:
        person2_ids2 = tuple(idx for idx in person2_ids)
      else:
        id_2 = [idx for idx in person2_ids[0:2]]
        person2_ids2 = (id_2[0], id_2[0])

      # store all this in a list
      stored_entities.append(
        [x, # original text
        tokens, # tokens
        person1[0], # person 1 name
        person2[0], # person 2 name
        person1_ids2, # person 1 id token tuple
        person2_ids2 # person 2 id token tuple
        ])

DF['sentences'].apply(get_entities)

# create dataframe in snorkel structure
DF_dev = pd.DataFrame(stored_entities, columns = ["sentence",
"tokens", "person1", "person2", "person1_word_idx",
"person2_word_idx"])
```

figure out where to look (between and to the left)

```
# live locate home road roads in at street (locations tied together)
# family terms for people

# get words between the data points
@preprocessor()
def get_text_between(cand: DataPoint) -> DataPoint:
    """
    Returns the text between the two person mentions in the sentence
```

```
    """
    start = cand.person1_word_idx[1] + 1
    end = cand.person2_word_idx[0]
    cand.between_tokens = cand.tokens[start:end]
    return cand

# get words next to the data points
@preprocessor()
def get_left_tokens(cand: DataPoint) -> DataPoint:
    """
    Returns tokens in the length 3 window to the left of the person
mentions
    """
    # TODO: need to pass window as input params
    window = 5

    end = cand.person1_word_idx[0]
    cand.person1_left_tokens = cand.tokens[0:end][-1 - window : -1]

    end = cand.person2_word_idx[0]
    cand.person2_left_tokens = cand.tokens[0:end][-1 - window : -1]
    return cand
```

figure out what to look for

```
# live locate home road roads in at street (locations tied together)
# family terms for people

found_location = 1
found_family = -1
ABSTAIN = 0

location = {"live", "living", "locate", "located", "home", "road",
"roads", "street", "streets", "in", "at", "of"}

@labeling_function(resources=dict(location=location),
pre=[get_text_between])
def between_location(x, location):
    return found_location if
len(location.intersection(set(x.between_tokens))) > 0 else ABSTAIN

@labeling_function(resources=dict(location=location),
pre=[get_left_tokens])
def left_location(x, location):
    if len(set(location).intersection(set(x.person1_left_tokens))) >
0:
        return found_location
    elif len(set(location).intersection(set(x.person2_left_tokens))) >
0:
        return found_location
```

```
    else:
        return ABSTAIN

family = {"spouse", "wife", "husband", "ex-wife", "ex-husband",
"marry",
          "married", "father", "mother", "sister", "brother", "son",
"daughter",
          "grandfather", "grandmother", "uncle", "aunt", "cousin",
          "boyfriend", "girlfriend"}

@labeling_function(resources=dict(family=family),
pre=[get_text_between])
def between_family(x, family):
    return found_family if
len(family.intersection(set(x.between_tokens))) > 0 else ABSTAIN

@labeling_function(resources=dict(family=family),
pre=[get_left_tokens])
def left_family(x, family):
    if len(set(family).intersection(set(x.person1_left_tokens))) > 0:
        return found_family
    elif len(set(family).intersection(set(x.person2_left_tokens))) >
0:
        return found_family
    else:
        return ABSTAIN

# create a list of functions to run
lfs = [
    between_location,
    left_location,
    between_family,
    left_family
]
# build the applier function
applier = PandasLFApplier(lfs)
# run it on the dataset
L_dev = applier.apply(DF_dev)
```

```
100%|██████████| 49/49 [00:00<00:00, 669.47it/s]
```

```
L_dev
```

```
array([[0, 0, 0, 0],
       [0, 0, 0, 0],
       [0, 0, 0, 0],
       [0, 0, 0, 0],
       [0, 0, 0, 0],
       [0, 1, 0, 0],
       [0, 0, 0, 0],
```

```
       [0, 0, 0, 0],
       [0, 0, 0, 0],
       [0, 1, 0, 0],
       [0, 0, 0, 0],
       [1, 0, 0, 0],
       [0, 0, 0, 0],
       [0, 0, 0, 0],
       [0, 0, 0, 0],
       [0, 1, 0, 0],
       [0, 0, 0, 0],
       [0, 0, 0, 0],
       [0, 0, 0, 0],
       [0, 0, 0, 0],
       [0, 0, 0, 0],
       [0, 0, 0, 0],
       [1, 1, 0, 0],
       [0, 0, 0, 0],
       [0, 0, 0, 0],
       [0, 0, 0, 0],
       [1, 1, 0, 0],
       [0, 0, 0, 0],
       [0, 0, 0, 0],
       [1, 1, 0, 0],
       [0, 0, 0, 0],
       [1, 1, 0, 0],
       [1, 1, 0, 0],
       [0, 0, 0, 0],
       [1, 0, 0, 0],
       [0, 0, 0, 0],
       [0, 0, 0, 0],
       [0, 0, 0, 0],
       [0, 0, 0, 0],
       [0, 0, 0, 0],
       [0, 0, 0, 0],
       [0, 0, 0, 0],
       [1, 0, 0, 0],
       [1, 0, 0, 0],
       [0, 0, 0, 0],
       [0, 0, 0, 0],
       [0, 0, 0, 0],
       [1, 0, 0, 0],
       [1, 0, 0, 0]])
```

```
DF_combined = pd.concat([DF_dev, pd.DataFrame(L_dev, columns =
["location1", "location2", "family1", "family2"])], axis = 1)
DF_combined
```

```
                                             sentence  \
0   The two main sampling techniques used as per s...
1   Structured , semi -structured , and unstructur...
```

```
2   Volume , Velocity , Variety , Veracity , and V...
3   NLP stands for Natural Language Processing , w...
4   Correlation and covariance are two measures of...
5   Correlation is a measure of how two variables ...
6   The Hamming distance and the Levenshtein dista...
7   The Hamming distance and the Levenshtein dista...
8   The Hamming distance and the Levenshtein dista...
9   The number of bits that differ between two str...
10  The number of edit operations ( insert , delet...
11  Nunique function is an aggregation function in...
12                .Is SVM a classification Algorithm ?
13  Univariate analysis has one variable , whereas...
14  A Pandas Index is a mutable , ordered set that...
15  .List some benefits of using TensorFlow There ...
16  Wrapper method includes : • Forward selection ...
17  Filter method includes : • Chi-square • ANOVA ...
18  Below are the steps for building a decision tr...
19  Below are the steps for building a decision tr...
20  Below are the steps for building a decision tr...
21  Below are the steps for building a decision tr...
22  Below are the steps for building a decision tr...
23  Below are the steps for building a decision tr...
24  Below are the steps for building a decision tr...
25  Below are the steps for building a decision tr...
26  Below are the steps for building a decision tr...
27  Below are the steps for building a decision tr...
28  Below are the steps for building a decision tr...
29  Below are the steps for building a decision tr...
30  Below are the steps for building a decision tr...
31  Below are the steps for building a decision tr...
32  Below are the steps for building a decision tr...
33  .Give some drawbacks of linear regression mode...
34  Bivariate analysis is the study of two variabl...
35  X [ : , np.newaxis ] + Y .Solve the below code...
36  X [ : , np.newaxis ] + Y .Solve the below code...
37  X [ : , np.newaxis ] + Y .Solve the below code...
38  X [ : , np.newaxis ] + Y .Solve the below code...
39  X [ : , np.newaxis ] + Y .Solve the below code...
40  X [ : , np.newaxis ] + Y .Solve the below code...
41  X [ : , np.newaxis ] + Y .Solve the below code...
42  X [ : , np.newaxis ] + Y .Solve the below code...
43  X [ : , np.newaxis ] + Y .Solve the below code...
44  X [ : , np.newaxis ] + Y .Solve the below code...
45  The probability is / .Using the Euclidean dist...
46  For : ( X , Y ) = (  ,  ) ( X , Y ) = (  ,  ) ...
47  For : ( X , Y ) = (  ,  ) ( X , Y ) = (  ,  ) ...
48  For : ( X , Y ) = (  ,  ) ( X , Y ) = (  ,  ) ...

                                               tokens  \
```

```
0   [The, two, main, sampling, techniques, used, a...
1   [Structured, ,, semi, -structured, ,, and, uns...
2   [Volume, ,, Velocity, ,, Variety, ,, Veracity,...
3   [NLP, stands, for, Natural, Language, Processi...
4   [Correlation, and, covariance, are, two, measu...
5   [Correlation, is, a, measure, of, how, two, va...
6   [The, Hamming, distance, and, the, Levenshtein...
7   [The, Hamming, distance, and, the, Levenshtein...
8   [The, Hamming, distance, and, the, Levenshtein...
9   [The, number, of, bits, that, differ, between,...
10  [The, number, of, edit, operations, (, insert,...
11  [Nunique, function, is, an, aggregation, funct...
12        [.Is, SVM, a, classification, Algorithm, ?]
13  [Univariate, analysis, has, one, variable, ,, ...
14  [A, Pandas, Index, is, a, mutable, ,, ordered,...
15  [.List, some, benefits, of, using, TensorFlow,...
16  [Wrapper, method, includes, :, •, Forward, sel...
17  [Filter, method, includes, :, •, Chi, -, squar...
18  [Below, are, the, steps, for, building, a, dec...
19  [Below, are, the, steps, for, building, a, dec...
20  [Below, are, the, steps, for, building, a, dec...
21  [Below, are, the, steps, for, building, a, dec...
22  [Below, are, the, steps, for, building, a, dec...
23  [Below, are, the, steps, for, building, a, dec...
24  [Below, are, the, steps, for, building, a, dec...
25  [Below, are, the, steps, for, building, a, dec...
26  [Below, are, the, steps, for, building, a, dec...
27  [Below, are, the, steps, for, building, a, dec...
28  [Below, are, the, steps, for, building, a, dec...
29  [Below, are, the, steps, for, building, a, dec...
30  [Below, are, the, steps, for, building, a, dec...
31  [Below, are, the, steps, for, building, a, dec...
32  [Below, are, the, steps, for, building, a, dec...
33  [.Give, some, drawbacks, of, linear, regressio...
34  [Bivariate, analysis, is, the, study, of, two,...
35  [X, [, :, ,, np.newaxis, ], +, Y, .Solve, the,...
36  [X, [, :, ,, np.newaxis, ], +, Y, .Solve, the,...
37  [X, [, :, ,, np.newaxis, ], +, Y, .Solve, the,...
38  [X, [, :, ,, np.newaxis, ], +, Y, .Solve, the,...
39  [X, [, :, ,, np.newaxis, ], +, Y, .Solve, the,...
40  [X, [, :, ,, np.newaxis, ], +, Y, .Solve, the,...
41  [X, [, :, ,, np.newaxis, ], +, Y, .Solve, the,...
42  [X, [, :, ,, np.newaxis, ], +, Y, .Solve, the,...
43  [X, [, :, ,, np.newaxis, ], +, Y, .Solve, the,...
44  [X, [, :, ,, np.newaxis, ], +, Y, .Solve, the,...
45  [The, probability, is, /, .Using, the, Euclide...
46  [For, :, (, X, ,, Y, ), =, (,  , ,,  , ), (, X...
47  [For, :, (, X, ,, Y, ), =, (,  , ,,  , ), (, X...
48  [For, :, (, X, ,, Y, ), =, (,  , ,,  , ), (, X...
```

```
                                               person1  \
0                                                  two
1                                           Structured
2                                                Value
3                                                  NLP
4                                                  two
5                                                  two
6                                          Levenshtein
7                                          Levenshtein
8                                                  two
9                                                  two
10                                                 one
11                                             Nunique
12                                                 SVM
13                                                 one
14                                              Pandas
15                                          TensorFlow
16                                                 One
17                                        • Chi-square
18                                         • Calculate
19                                         • Calculate
20                                         • Calculate
21                                         • Calculate
22                                         • Calculate
23                                         • Calculate
24                                         • Calculate
25                                         • Calculate
26                                         • Calculate
27                                         • Calculate
28                                         • Calculate
29                                         • Calculate
30                                            • Select
31                                            • Select
32                                            • Repeat
33                                              linear
34                                           Bivariate
35                                             Biotech
36                                             Biotech
37                                             Biotech
38                                             Biotech
39                                               years
40                                               years
41                                               years
42   SELECT Name FROM StudentData WHERE Department ...
43   SELECT Name FROM StudentData WHERE Department ...
44                                               three
45                                           Euclidean
46                                                 ROC
```

```
47                                               ROC
48                                     Build Looking

                                             person2 person1_word_idx
\
0                                              • Non           (1, 1)

1                                              three           (0, 0)

2                                               five           (9, 9)

3                        Natural Language Processing           (0, 0)

4                                                two           (4, 4)

5                                                two           (6, 6)

6                                                two           (5, 5)

7                                                two           (5, 5)

8                                                two           (8, 8)

9                                            Hamming           (7, 7)

10                                       Levenshtein         (17, 17)

11                                        PostgreSQL           (0, 0)

12                                         Algorithm           (1, 1)

13                                               two           (3, 3)

14                                  Pandas DataFrame           (1, 1)

15                                        TensorFlow           (5, 5)

16                                        • Backward           (8, 8)

17                                          • Filter           (4, 5)

18                                       • Calculate         (18, 19)

19                                       • Calculate         (18, 19)

20                                          • Select         (18, 19)

21                                          • Repeat         (18, 19)

22                                               INR         (18, 19)
```

23	• Calculate	(18, 19)
24	• Select	(18, 19)
25	• Repeat	(18, 19)
26	INR	(18, 19)
27	• Select	(18, 19)
28	• Repeat	(18, 19)
29	INR	(18, 19)
30	• Repeat	(18, 29)
31	INR	(18, 29)
32	INR	(18, 29)
33	linear	(4, 4)
34	two	(0, 0)
35	years	(71, 71)
36	SELECT Name FROM StudentData WHERE Department ...	(71, 71)
37	three	(71, 71)
38	two	(71, 71)
39	SELECT Name FROM StudentData WHERE Department ...	(76, 76)
40	three	(76, 76)
41	two	(76, 76)
42	three	(12, 40)
43	two	(12, 40)
44	two	(100, 100)
45	P	(6, 6)
46	Build Looking	(29, 29)
47	US	(29, 29)
48	US	(33, 34)

	person2_word_idx	location1	location2	family1	family2
0	(12, 26, 27)	0	0	0	0
1	(10, 10)	0	0	0	0
2	(12, 12)	0	0	0	0
3	(3, 4)	0	0	0	0
4	(4, 4)	0	0	0	0
5	(6, 6)	0	1	0	0
6	(8, 8)	0	0	0	0
7	(8, 8)	0	0	0	0
8	(8, 8)	0	0	0	0
9	(13, 13)	0	1	0	0
10	(25, 25)	0	0	0	0
11	(7, 7)	1	0	0	0
12	(4, 4)	0	0	0	0
13	(10, 10)	0	0	0	0
14	(1, 18, 19)	0	0	0	0
15	(5, 5)	0	1	0	0
16	(4, 23, 24)	0	0	0	0
17	(0, 4, 8, 10, 14, 15)	0	0	0	0
18	(18, 19, 29, 30, 36, 37, 44, 56)	0	0	0	0
19	(18, 19, 29, 30, 36, 37, 44, 56)	0	0	0	0
20	(18, 29, 36, 44, 45, 56)	0	0	0	0
21	(18, 29, 36, 44, 56, 57)	0	0	0	0
22	(128, 128)	1	1	0	0

```
23  (18, 19, 29, 30, 36, 37, 44, 56)          0          0         0
0
24          (18, 29, 36, 44, 45, 56)          0          0         0
0
25          (18, 29, 36, 44, 56, 57)          0          0         0
0
26                        (128, 128)          1          1         0
0
27          (18, 29, 36, 44, 45, 56)          0          0         0
0
28          (18, 29, 36, 44, 56, 57)          0          0         0
0
29                        (128, 128)          1          1         0
0
30          (18, 29, 36, 44, 56, 57)          0          0         0
0
31                        (128, 128)          1          1         0
0
32                        (128, 128)          1          1         0
0
33                            (4, 4)          0          0         0
0
34                            (6, 6)          1          0         0
0
35                          (76, 76)          0          0         0
0
36                  (40, 41, 78, 79)          0          0         0
0
37                        (100, 100)          0          0         0
0
38                        (109, 109)          0          0         0
0
39                  (40, 41, 78, 79)          0          0         0
0
40                        (100, 100)          0          0         0
0
41                        (109, 109)          0          0         0
0
42                        (100, 100)          1          0         0
0
43                        (109, 109)          1          0         0
0
44                        (109, 109)          0          0         0
0
45                          (16, 16)          0          0         0
0
46                          (33, 34)          0          0         0
0
47                          (40, 40)          1          0         0
0
```

```
48                          (40, 40)          1          0         0
0

DF_combined['location_yes'] = DF_combined['location1'] +
DF_combined["location2"]
DF_combined['family_yes'] = DF_combined['family1'] +
DF_combined["family2"]

print(DF_combined['location_yes'].value_counts())
print(DF_combined['family_yes'].value_counts())
print(DF_combined.head())
DF_combined.to_csv('family_check.csv', index=False)

location_yes
0    35
1     9
2     5
Name: count, dtype: int64
family_yes
0    49
Name: count, dtype: int64
                                            sentence  \
0  The two main sampling techniques used as per s...
1  Structured , semi -structured , and unstructur...
2  Volume , Velocity , Variety , Veracity , and V...
3  NLP stands for Natural Language Processing , w...
4  Correlation and covariance are two measures of...

                                              tokens     person1  \
0  [The, two, main, sampling, techniques, used, a...         two
1  [Structured, ,, semi, -structured, ,, and, uns...  Structured
2  [Volume, ,, Velocity, ,, Variety, ,, Veracity,...       Value
3  [NLP, stands, for, Natural, Language, Processi...         NLP
4  [Correlation, and, covariance, are, two, measu...         two

                       person2 person1_word_idx person2_word_idx
location1  \
0                        • Non           (1, 1)     (12, 26, 27)
0
1                        three           (0, 0)         (10, 10)
0
2                         five           (9, 9)         (12, 12)
0
3  Natural Language Processing           (0, 0)           (3, 4)
0
4                          two           (4, 4)           (4, 4)
0

   location2  family1  family2  location_yes  family_yes
0          0        0        0             0           0
```

```
1            0        0        0             0           0
2            0        0        0             0           0
3            0        0        0             0           0
4            0        0        0             0           0
```

- What might you do to improve the default NER extraction?

Knowledge Graphs

Slides Version

- Based on the chosen text, add entities to a default spacy model.
- Add a norm_entity, merge_entity, and init_coref pipelines.
- Update and add the alias lookup if necessary for the data.
- Add the name resolver pipeline.

Or Use Your Snorkel Output

- Create a co-occurrence graph of the entities linked together in your text.

```
# locations only
DF_loc = DF_combined[DF_combined['location_yes'] > 0]
DF_loc = DF_loc[['person1', 'person2']].reset_index(drop = True)

cooc_loc = DF_loc.groupby(by=["person1", "person2"],
as_index=False).size()

# family only
DF_combined['family_yes'] = DF_combined['family_yes'].abs()

DF_fam = DF_combined[DF_combined['family_yes'] > 0]
DF_fam = DF_fam[['person1', 'person2']].reset_index(drop = True)

#print(DF_fam.head())

cooc_fam = DF_fam.groupby(by=["person1", "person2"],
as_index=False).size()

# take out issues where entity 1 == entity 2
cooc_loc = cooc_loc[cooc_loc['person1'] != cooc_loc['person2']]
cooc_fam = cooc_fam[cooc_fam['person1'] != cooc_fam['person2']]

print(cooc_loc.head())
print(cooc_fam.head())
```

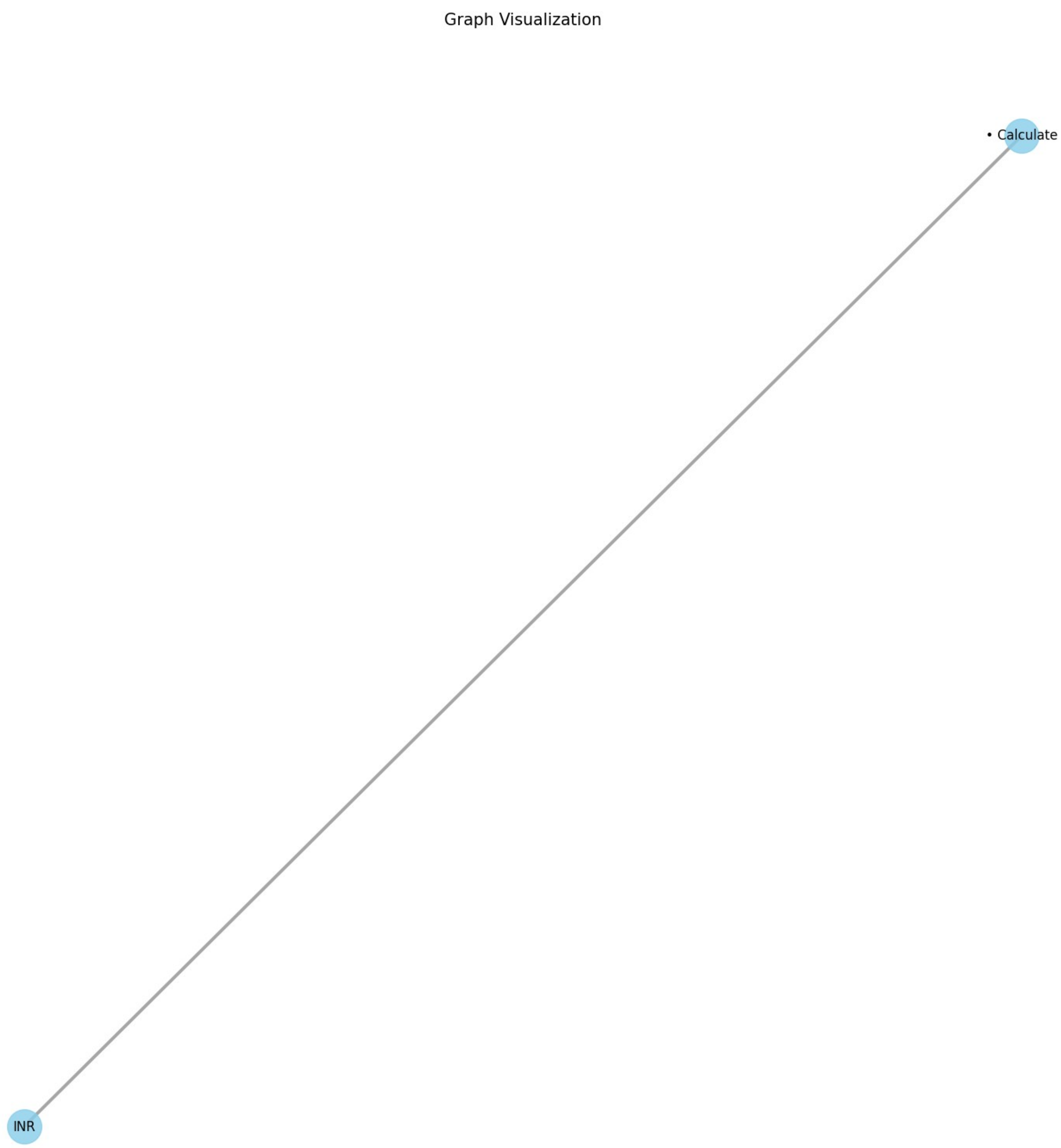
```
                                       person1     person2  size
0                                    Bivariate         two     1
1                               Build Looking           US     1
```

```
2                                                        Nunique  PostgreSQL     1
3                                                            ROC          US     1
4  SELECT Name FROM StudentData WHERE Department ...       three     1
Empty DataFrame
Columns: [person1, person2, size]
Index: []
```

- This creates a dataframe of node 1 and then node 2 (entity 1 to entity 2) and then frequency (size)

```
# start by plotting the whole thing for location
# cooc_loc_small = cooc_loc[cooc_loc['size']>1]
# graph = nx.from_pandas_edgelist(
#             cooc_loc_small[['person1', 'person2', 'size']] \
#             .rename(columns={'size': 'weight'}),
#             source='person1', target='person2', edge_attr=True)

# pos = nx.kamada_kawai_layout(graph, weight='weight')

# _ = plt.figure(figsize=(20, 20))
# nx.draw(graph, pos,
#         node_size=1000,
#         node_color='skyblue',
#         alpha=0.8,
#         with_labels = True)
# plt.title('Graph Visualization', size=15)

# for (node1,node2,data) in graph.edges(data=True):
#     width = data['weight']
#     _ = nx.draw_networkx_edges(graph,pos,
#                                edgelist=[(node1, node2)],
#                                width=width,
#                                edge_color='#505050',
#                                alpha=0.5)

# plt.show()
# plt.close()

# # start by plotting the whole thing for location
# graph = nx.from_pandas_edgelist(
#             cooc_fam[['person1', 'person2', 'size']] \
#             .rename(columns={'size': 'weight'}),
#             source='person1', target='person2', edge_attr=True)

# pos = nx.kamada_kawai_layout(graph, weight='weight')

# _ = plt.figure(figsize=(20, 20))
# nx.draw(graph, pos,
#         node_size=1000,
#         node_color='skyblue',
```

```
#         alpha=0.8,
#         with_labels = True)
# plt.title('Graph Visualization', size=15)

# for (node1,node2,data) in graph.edges(data=True):
#     width = data['weight']
#     _ = nx.draw_networkx_edges(graph,pos,
#                                 edgelist=[(node1, node2)],
#                                 width=width,
#                                 edge_color='#505050',
#                                 alpha=0.5)

# plt.show()
# plt.close()

# Filter the data
cooc_loc_small = cooc_loc[cooc_loc['size'] > 1]

# Create the graph from the filtered dataframe
graph = nx.from_pandas_edgelist(
    cooc_loc_small,
    source='person1',
    target='person2',
    edge_attr='size'
)

# Generate positions for each node using Kamada-Kawai layout
considering the edge weights
pos = nx.kamada_kawai_layout(graph, weight='size')

# Plotting
plt.figure(figsize=(20, 20))
# Draw nodes
nx.draw_networkx_nodes(graph, pos, node_size=1000,
node_color='skyblue', alpha=0.8)
# Draw labels
nx.draw_networkx_labels(graph, pos)
# Draw edges
edges = nx.draw_networkx_edges(graph, pos, edge_color='#505050',
alpha=0.5,
                               width=[data['size'] for _, _, data in
graph.edges(data=True)])

plt.title('Graph Visualization', size=15)
plt.axis('off')  # Turn off the axis
plt.show()
```




```
print(cooc_fam.head())

Empty DataFrame
Columns: [person1, person2, size]
Index: []

# Filter the data
cooc_fam

# Create the graph from the filtered dataframe
graph = nx.from_pandas_edgelist(
    cooc_fam,
```

```
    source='person1',
    target='person2',
    edge_attr='size'
)

# Generate positions for each node using Kamada-Kawai layout
considering the edge weights
pos = nx.kamada_kawai_layout(graph, weight='size')

# Plotting
plt.figure(figsize=(20, 20))
# Draw nodes
nx.draw_networkx_nodes(graph, pos, node_size=1000,
node_color='skyblue', alpha=0.8)
# Draw labels
nx.draw_networkx_labels(graph, pos)
# Draw edges
edges = nx.draw_networkx_edges(graph, pos, edge_color='#505050',
alpha=0.5,
                               width=[data['size'] for _, _, data in
graph.edges(data=True)])

plt.title('Graph Visualization', size=15)
plt.axis('off')  # Turn off the axis
plt.show()
```

Graph Visualization

I had to make couple of changes in code.Some libraries were not working due to compatibility issues. graphs were not being plotted.Also, Family df was empty df hence converted -ve numbers to +ve.(we were using family_yes > 0 and numbers were 0,-1,-2. We could have solved it by family_yes < 0 but it could have caused issus futher due to -ve numbers hence made +ve)

The most common part of speech in the analyzed text is NOUN, with a total count of 10,799 occurrences.There are multiple parts of the speech.

The key phrase extraction outputs from Textacy and Summa show distinct characteristics. Textacy's output includes specific phrases like 'old man Marsh' and 'old Captain Obed Marsh', which seem directly extracted from the text. It also combines similar terms into sets, indicating an attempt to consolidate variations of key phrases.Summa's output, represented by the TR_keywords, includes more granular terms like 'things' and 'streets', with associated scores indicating their relevance. The terms are more individualized and not grouped into phrases, suggesting Summa focuses on singular keywords rather than multi-word phrases.

The differences indicate that Textacy might be better suited for extracting and consolidating multi-word key phrases,while Summa appears to emphasize the importance of individual terms within the text. Given the context, Textacy's approach might provide more contextual insights into the text's themes, whereas Summa offers a breakdown of key terms by their significance.

To enhance default NER extraction, we can train the model with domain-specific data and incorporating contextual rules for better entity recognition.